

Article

A Preliminary Study on the Utilization of Hyperspectral Imaging for the On-Soil Recognition of Plastic Waste Resulting from Agricultural Activities

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Abstract: Plastic in agriculture is frequently used to protect crops and its use boosts output, enhances food quality, contributes to minimize water consumption, and reduces the environmental impacts of agricultural activities. On the other hand, end-of-life plastic management and disposal are the main issues related to their presence in this kind of environment, especially in respect of plastic degradation, if not properly handled (i.e., storage places directly in contact with the ground, exposure of stocks to meteoric agents for long periods, incorrect or incomplete removal). In this study, the possibility of using an in situ near infrared (NIR: 1000–1700 nm) hyperspectral imaging detection architecture for the recognition of various plastic wastes in agricultural soils in order to identify their presence and also assess their degradation from a recovery/recycling perspective was explored. In more detail, a Partial Least Squares—Discriminant Analysis (PLS-DA) classifier capable of identifying plastic waste from soil was developed, implemented, and set up. Results showed that hyperspectral imaging, in combination with chemometric approaches, allows the utilization of a rapid, non-destructive, and non-invasive analytical approach for characterizing the plastic waste produced in agriculture, as well as the potential assessment of their lifespan.

Keywords: hyperspectral imaging; plastic waste; on-soil recognition; agricultural activity



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1. Introduction

The number of plastic debris dispersed or left on soil is a growing concern, since it might potentially exceed several times the quantities lost in waterways and seas. On the other hand, plastic in the soil has a negative effect on crop growth. In agriculture, many plastic products are adopted, such as mulching sheets, fertilizer bags, irrigation pipes, pesticide containers, and protective nets. In more detail, a wide range of plastic types are employed, including polyolefins (PO), polyethylenes (PE), polypropylenes (PP), and ethylene-vinyl acetate copolymers (EVA), as well as less commonly used materials such as polyvinyl chloride (PVC), polycarbonate (PC), and polymethyl methacrylate (PMMA).

In agriculture, the use of plastic shows several advantages but also drawbacks, which are discussed in the following sections. Numerous key properties of plastic materials, such as their light weight, ease of use, versatility, durability, low purchase price (i.e., cost-effectiveness), low cost of installation and maintenance, and excellent mechanical resistance, have led to their widespread and expanding use [1,2]. The main benefits related to plastic use in agriculture include protection from climatic variations, a more effective use of water and farmland, an improvement in the quality and quantity of crops, a decrease in the usage of weed killers, and earlier or later harvests [3–5]. All these

conditions are mainly realized through greenhouse cultivation. Greenhouses, in fact, utilize solar energy to create a favorable indoor microclimate, optimizing the growth and development conditions of the plants. Plant development and productivity are impacted by changes in the spectral wavelength distribution and quantity of solar light that pass through nets and films. These changes affect how plants respond in terms of photosynthetic, photomorphogenetic, phototropic, and photoperiodic processes [6,7]. Plastic sheets used for greenhouse covers, therefore, play a primary role. Even though all of this may appear to have a beneficial side, it could also represent a source of land contamination. In a sustainable agriculture perspective, optimal soil health represents the paramount objective to achieve. This objective is strongly influenced by the utilization of plastic-coated fertilizers and plastic-contained sludge water, both of which pose detrimental effects on soil health, agricultural productivity, and human well-being within agricultural areas.

The increasing use of plastic in agriculture thus produces negative impacts on environmental sustainability related to the production of many polymer-based post-consumer materials that are disposed of inappropriately. Plastics are, in fact, characterized by a relatively short “operative lifespan”. Films are affected by a progressive deterioration of their properties because of their thickness, their exposure to solar radiation and pesticides, and meteorological variations. Therefore, the frequent replacement of films and the utilization of other plastics generate a large amount of post-consumer material that must be properly managed [8,9]. The improper disposal of these plastics and the further generation of microplastics (MPs), that is, plastic debris with a size dimension less than 5 mm, can cause important environmental issues, particularly in areas with a delicate ecology and a strong tourism industry. For these reasons, it is of great importance to recognize and classify plastic fragments of larger dimension before they became a source of microplastics production due to their physical alterations. The primary sources of high microplastic dispersion in the terrestrial ecosystem include, in fact, the use of plastic mulch, tunnels, sewage sludge, fertilizer bags, shade, flood and street runoff, and atmospheric fallout [10–13]. Due to its widespread use in agriculture, plastic mulching represents the main source of MPs generation.

The main issue with mulching applications is that, because they only last one cycle of cultivation, they have a short lifespan (between 3 and 8 months). Additionally, due to their thickness, they break readily and are quickly assimilated into the soil [10]. The majority of the plastic mulch utilized is left in the soil after crop harvesting, when it is gradually fragmented by mechanical abrasion and ultraviolet radiation [14,15]. Consequently, improper handling and disposal of plastic products and waste plastics in agricultural activities can cause the accumulation of MPs in soil or in meat (i.e., biomass feeding contamination). Therefore, plastics can be transferred to the food chain, posing a risk to the health of living beings, including humans [16].

For these reasons, a non-invasive, non-destructive, and field-applicable technique to carry out systematic soil monitoring in agricultural areas to detect and topologically assess plastic fragments for their subsequent collection and separation is needed. Such an approach could be profitably carried out prior to the transformation of plastic fragments into MPs to make the procedures of soil cleaning and reclamation easier.

The main techniques for identifying plastic debris and MPs are visual characterization and vibrational spectroscopy [17]. Visual characterization is a simple and cost-effective technique [18]. However, user subjectivity makes visual characterization difficult, making it possible for small particles to be overlooked or misunderstood. MPs identification can be carried out by traditional microscopy, while smaller MPs (<200 nm) can be analysed by scanning electron microscopy (SEM). However, SEM is quite expensive and the associated sample preparation is time-consuming [19]. The most common and advanced analytical methods for studying MPs are Raman spectroscopy and Fourier transform infrared spectroscopy (FTIR). They can discern the distinction between polymers and other substances in a sample and identify the type of polymer.

A simple and inexpensive method for identifying MPs is FTIR. The size of FTIR-recognition MPs is nevertheless constrained. FTIR spectra must be compared to the spectrum library and carefully analysed in order to increase the accuracy of MPs identification [20]. Since the chemical imaging line produced by Raman spectroscopy can have a pixel resolution of 500 nm, it can compensate for some of FTIR's drawbacks [21].

In this paper, an innovative detection approach based on HyperSpectral Imaging (HSI) in the Near InfraRed (NIR) range is proposed.

NIR-HSI provides NIR spectral data in the form of a series of images, each representing a certain wavelength range or spectrum band [22]. One notable advantage of using NIR spectroscopy in conjunction with imaging techniques is the incorporation of an additional spatial dimension. This enables the analysis and visualization of images as a chemical 2D domain, facilitating the identification and localization of distinct materials within heterogeneous samples. NIR-HSI has the potential to be effectively utilized both “in situ” and at the laboratory scale. Its ability to provide rapid and non-destructive analysis significantly reduces sampling and analytical time compared to traditional methods.

This technique is widely used in the industrial field, in the agri-food and in the recycling sector for quality control and process monitoring [23,24]. HSI, along with chemometrics, combines the benefits of conventional spectroscopy with those of classical image analysis and has been applied by different authors to study plastic degradation [25] and classify plastics [26,27]. Moreover, recent studies were carried out in order to detect MPs in farmland soil by hyperspectral techniques using portable and laboratory instrumentations [28–30] or by satellite imagery analysis [31,32].

However, to the best of our knowledge, no studies on the on-soil detection of plastic fragments (>5 mm) used for agricultural activities to early and locally detect possible MPs dispersion have been carried out. The main goals of this preliminary study were thus to develop a sensor-based system able: (i) to detect and identify plastics in soil, (ii) to define a suitable classification strategy for their recognition/classification, and (iii) to evaluate the investigated plastic lifespan (i.e., aging). HSI in the Near InfraRed (NIR: 1000–1700 nm) range was used to accomplish these objectives. The spectra of the different analysed plastic debris and soils, collected in the NIR interval, provide chemical information on their composition, being the spectral signatures linked with the absorption bands of the functional groups CH, OH, and NH [33]. The present work has to be considered an investigation, setting up the basis for the potential to identify the various types of involved polymers.

2. Materials and Methods

Soil samples and degraded plastics were acquired with the ImSpector™ N17E (Specim, Spectral Imaging Ltd., Oulu, Finland) hyperspectral imaging analytical device. Then, chemometric procedures were carried out for the identification of plastics in the soil and to evaluate their aging. The collected hyperspectral images were then pre-processed to attenuate noisy effects due to detector and/or scattering phenomena, remove dead pixels, and enhance spectra differences. A Principal Component Analysis (PCA) was then performed for the exploratory analysis [34] of the acquired data. Finally, Partial Least Squares—Discriminant Analysis (PLS-DA) was performed for classification purposes [35].

A schematic diagram of the described approach is reported in Figure 1.

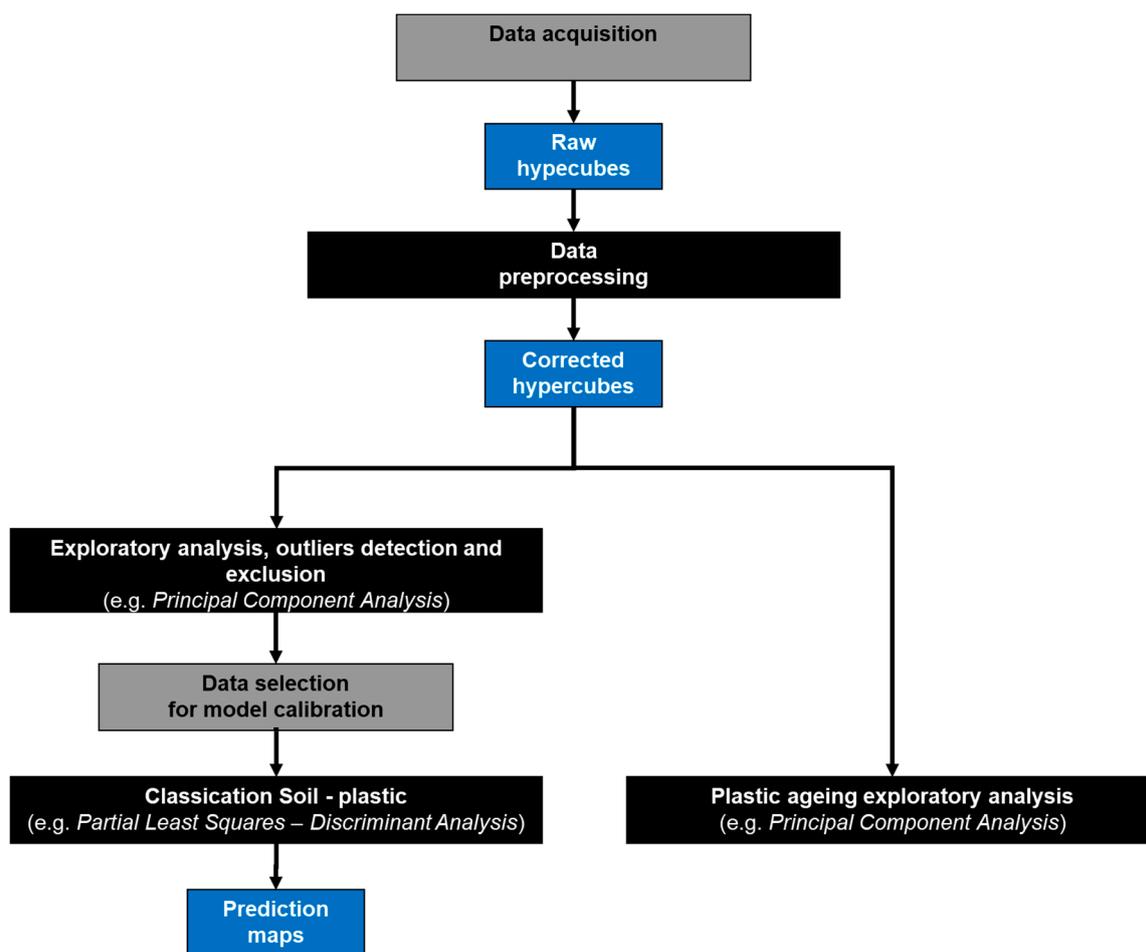


Figure 1. Schematic diagram of the developed approach.

2.1. Sample Preparation and Experimental Set-Up

Analysed soil and plastic samples were provided from a farm in Sabaudia (Italy), next to the Circeo National Park protected area. This farm mainly produces horticultural products and during its various activities, different polymeric materials are used: sheets for covering greenhouses, sheets for mulching, and hoses for irrigation of the horticultural products. In this context, in order to develop a PLS-DA classifier able to detect plastics mixed with soil, both samples of plastic used for agricultural activities and soil were analysed.

The analysed polymeric samples (size dimension > 5 mm) are composed of polyethylene (PE), polypropylene (PP), ethylene vinyl acetate (EVA), and biodegradable plastics and they were divided according to their level of degradation, referred to as the time of use. Seven samples of polymeric products were thus collected and utilized to build their spectral reference-training set for the classification model (Figure 2). The seven samples being constituted by PE irrigation hose fragments (one “unused” and one “used for a year”), EVA greenhouse cover fragments (one “unused” and one “used for 5 years”), PP mulch sheet fragments (one “unused” and one “used for 3 years”), and a fragment of biodegradable mulch sheet (never used).

Since the investigated area is about 20,000 m², six soil collection points were chosen to be investigated according to regulatory suggestions [36]. Six samples of soil (topsoil), mostly medium-coarse sand (Figure 3), were collected from different locations on the farm. Three samples were collected inside each greenhouse of the farm, while three samples were taken in the external area. Soil sampling was performed by coning and quartering.

Following sampling, the adopted hyperspectral equipment was used to acquire the soils in Petri dishes (100 mm × 15 mm) in order to build the model training set.

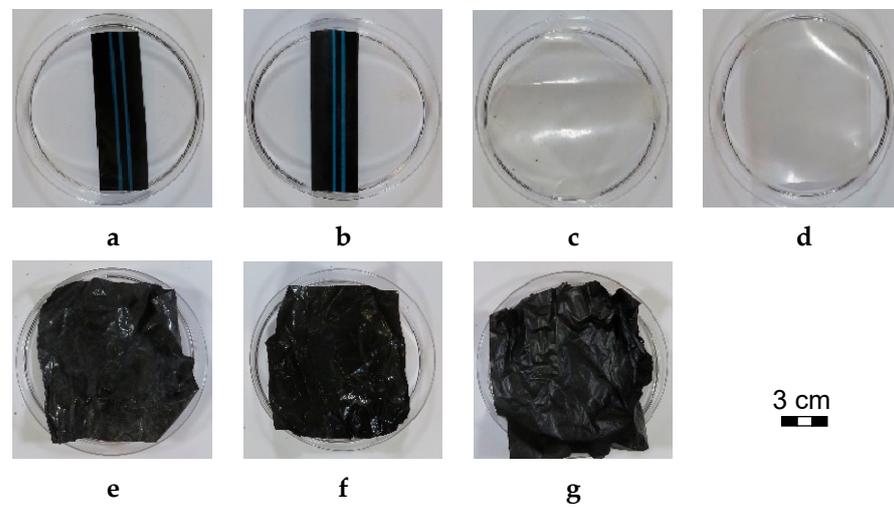


Figure 2. Samples of polymeric products: (a) PE—new, (b) PE—1 year of use, (c) EVA—5 years of use, (d) EVA—new, (e) PP—3 years of use, (f) PP—new, (g) biodegradable plastic—new.

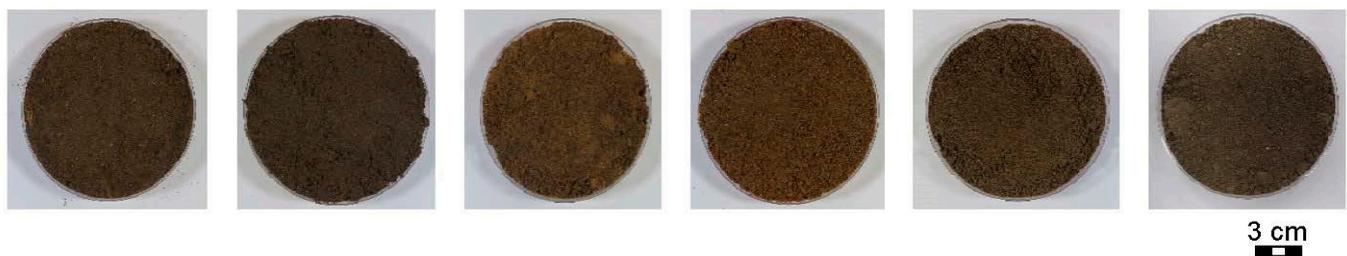


Figure 3. Soil samples (topsoil) set.

Finally, four random samples of soil contaminated by plastics were collected and acquired (Figure 4) to obtain the validation images for the classification purpose. The contaminant samples were collected from the end-of-life plastic storage and accumulation area, exposed to the action of atmospheric agents. In more detail, this second set of samples was used to evaluate the classification model performance.

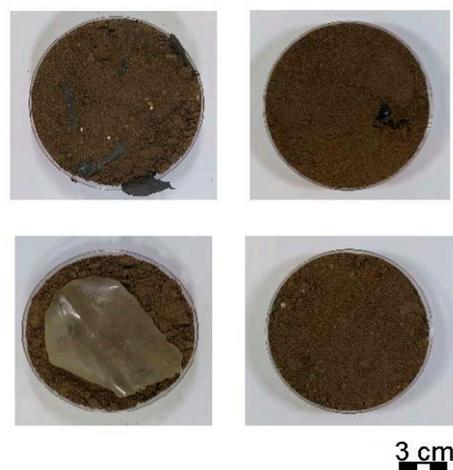


Figure 4. Set of soil validation samples.

2.2. Hyperspectral Imaging System (HSI) and Data Collection

An NIR Spectral Camera system (Specim, Spectral Imaging Ltd., Oulu, Finland), equipped with the ImSpector N17E spectrograph (1000–1700 nm) was used to capture hyperspectral images of each sample. The imaging spectrograph, based on a temperature-stabilized InGaAs photodiode array (320 × 240 pixels), has a spectral sampling/pixel of 3.3 nm and a spectral resolution of 5 nm, acquiring a field of view of 195 mm. This HSI system works as a push-broom scanning camera, enabling the collection of spectral data for each pixel of the line. The conveyor belt, on which the samples are placed, has dimensions of 26 cm in width and 160 cm in length. It has the capability to operate at different speeds, ranging from 0 mm/s to 50 mm/s. A diffused light cylinder with five halogen lamps produces a continuous spectrum signal that is designed for the capture of spectra in the NIR wavelength range, providing the energy needed for the hyperspectral imaging process. The HSI system is controlled by a personal computer running Spectral Scanner software (Ver. 2.3; DV S.r.l., Padova, Italy), which enables the acquisition, the collection, and the preliminary spectra handling. The hyperspectral data were acquired after an appropriate calibration of the system. Seven hyperspectral images for plastic (Figure 2) and six for soil (Figure 3) samples were acquired, respectively. The calibration dataset was then built from these thirteen images, while the validation set was built from the other four hyperspectral images collected on the samples reported in Figure 4.

2.3. Analysis of Hyperspectral Data

PLS_toolbox (Ver.9.0; Eigenvector Research, Inc., Wenatchee, WA, USA) and MIA_toolbox (Ver. 3.1; Eigenvector Research, Inc., Wenatchee, WA, USA) in the MATLAB environment (Ver. 7.5; The Mathworks, Inc., Natick, MA, USA) were used to analyse the hyperspectral images.

The calibration dataset was built from the hyperspectral images acquired for plastics and soil. The background was removed from each hyperspectral image and reflectance spectra were extracted in order to build a unique calibration dataset. The resulting calibration dataset has a size of 241,538 × 161 (number of spectra × wavelength channel): 98,863 spectra for plastics and 142,675 spectra for soil, respectively. The validation dataset was built by concatenating the hyperspectral images collected on the validation samples.

After a preliminary pre-processing of the hyperspectral data, chemometric techniques were applied. PCA was used to explore the variability of the defined classes (i.e., plastic and soil) and to evaluate the best algorithm to apply for the subsequent classification purposes by adopting a PLS-DA.

2.3.1. Pre-Processing of Hyperspectral Data

The spectral variables were limited to the wavelength range from 1000 to 1600 nm in order to exclude unwanted effects caused by instrument noise. Hyperspectral data were then pre-processed in order to highlight the spectral differences of the samples and reduce the impact of possible external sources of variability by adopting a sequential combination of two algorithms: the Standard Normal Variate (SNV) and the Mean Centring (MC) [37]. SNV is a weighted normalization algorithm that is usually adopted to solve the scale or gain effects. These phenomena can be due to path length effects, source diffusion effects, the physical nature of the material and particle size, variations of the source or detector, or other general effects of instrumental sensitivity. MC is one of the most common preprocessing methods that calculates the mean of each column and subtracts it from the column itself; each row of the mean-centred data includes only the difference between that row and the sample mean in the matrix of original data.

2.3.2. Principal Component Analysis (PCA)

PCA was applied to explore data analysis [34]. The PCA projects the samples into a low-dimensional subspace whose axes (the principal components, PCs) point in the direction of maximum variance, compressing the data. The differences and similarities

between the samples can be deduced by looking at how the samples are distributed in the space of the PCs. The more closely they are clustered, the more similar their spectral properties are. In addition, the PCA highlights the presence of trends between samples, providing preliminary information on the distribution of different samples on an image.

In the specific case study, PCA was adopted to evaluate the variability between the soil and plastic classes of the calibration set, identify any outliers, and prepare the calibration dataset for the classifier set up. Furthermore, this method was also applied to evaluate any variations in plastic debris spectral characteristics related to their degradation.

2.3.3. Partial Least Squares—Discriminant Analysis (PLS-DA)

PLS-DA was adopted to build a predictive model capable of distinguishing plastic debris from the soil. PLS-DA is one of the most commonly used data analysis methods for supervised sample classification based on conventional spectroscopy [35,38], balancing the quality of the achievable results in terms of recognition/classification with the processing speed and easiness of implementation. This method uses Partial Least Squares regression (PLSr) and is a linear method for supervised classification that requires prior knowledge of the data [39]. Starting from samples with known classes, a discriminant function is built to classify new unknown samples consisting of the same material as the known ones. Based on the similarity of the spectra, the PLS-DA model enables the assignment of only one of the possible classes to each unknown sample (in this case, a pixel). In order to assess the classifier's performance, *Sensitivity*, *Specificity*, *Precision*, *Error Rate*, and *Accuracy* were used [40]. In more detail, *Sensitivity* (Equation (1)) is the true positive rate, and it estimates the model's ability to avoid false negatives (FN) (i.e., the number of samples of a given type correctly classified). *Specificity* (Equation (2)) is the estimation of the model's ability to avoid false positives (FP) (the number of samples not of a particular type correctly classified as not of that type). *Precision* (Equation (3)) is the ratio of true positives (TP) to predicted positives, while the *Error Rate* (Equation (4)) shows how often outcomes are misclassified. Finally, model *Accuracy* (Equation (5)) is defined as the number of correct classifications predicted by a model, i.e., TP and true negatives (TN), divided by the total number of predictions produced. *Specificity*, *Precision*, *Error Rate*, and *Accuracy* were calculated for the calibration, cross-validation, and validation/testing phases of the modelling. The model was trained using the calibration dataset and tested on the validation dataset.

The Venetian Blinds (VB) algorithm was employed as a cross-validation technique to evaluate the optimal complexity of the models and determine the appropriate number of Latent Variables (LVs). In this case, four LVs were chosen.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (1)$$

$$\text{Specificity} = \frac{TN}{FP + TN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

$$\text{Error rate} = 1 - \text{Accuracy} = \frac{FP + FN}{TP + TN + FP + FN} \quad (4)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

3. Results and Discussion

3.1. Exploratory Analysis

The greatest differences between the soil and plastic classes are found in the wavelength ranges 1100–1200 nm and 1400–1500 nm. These ranges are specifically associ-

ated with the second overtone of the CH group and the first overtone of the OH group (Figure 5a) [33].

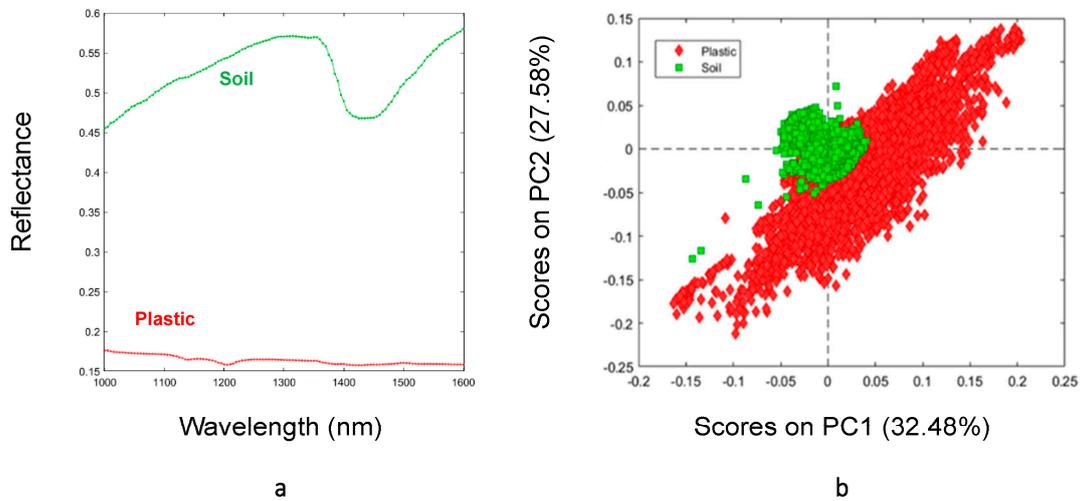


Figure 5. Mean raw spectra of plastic and soil (a) and PCA score plot related to the samples of calibration set (b).

In more detail, soil spectra have absorptions at 1410 nm assignable to OH first overtones. On the other hand, plastic spectra demonstrate absorption in the second overtone of CH within the range of 1100–1220 nm [41].

Indeed, the absorption of polymer compounds such as methylene (-CH₂-) and ethyl groups (-CH₃) occurs around 1210–1220 nm and 1195 nm, respectively [42].

These differences are further enhanced by the results of the PCA. Indeed, the plastic and soil categories form two separate score groups, although they partially overlap, as demonstrated by the graph in Figure 5b.

Different spectral characteristics are detectable in the different plastic debris spectra, also in relation to their aging (Figure 6a). From the PC1 vs. PC2 score plot (Figure 6b), a pattern regarding the state of aging of the plastic flakes is detectable. In this case, PC1 captured approximately 99% of the total variance of the dataset.

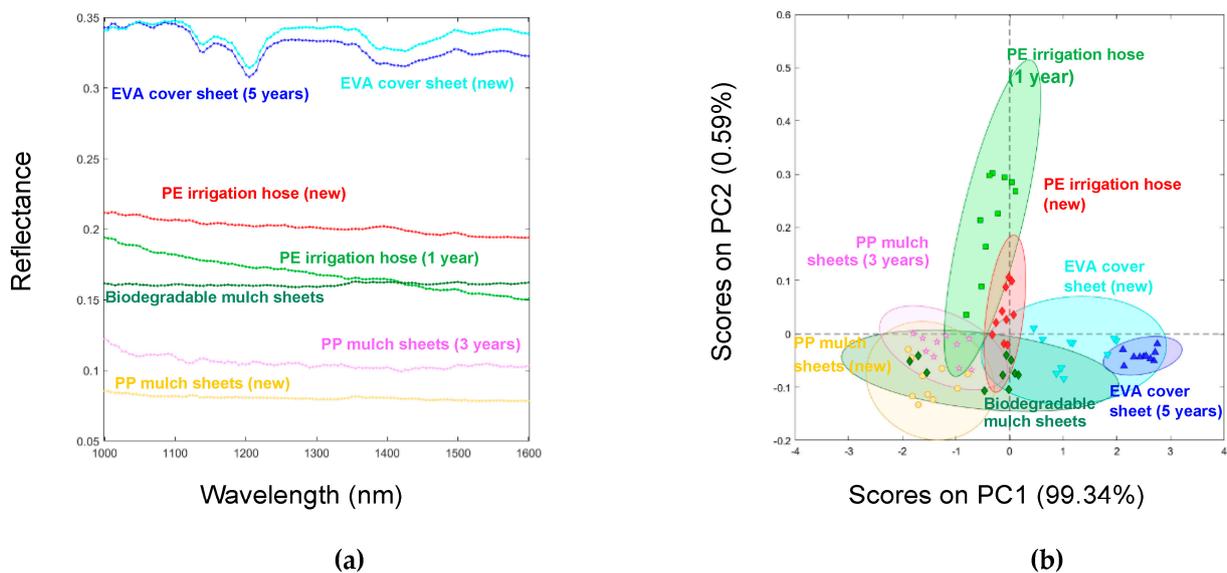


Figure 6. Mean raw spectra (a) and PCA score plot related to the set of polymer samples (b).

3.2. Recognition of Plastics from Soil

PLS-DA results are shown as prediction maps in Figure 7. Model *Sensitivity*, *Specificity*, *Precision*, and *Error Rate* are summarized in Table 1. The built model correctly distinguishes between plastic and soil. *Sensitivity* and *Specificity* for plastic are always greater than 0.92 in all three phases of the modelling. *Precision* for the plastic class is 0.99 in calibration and cross-validation and equal to 0.79 in prediction; on the other hand, *Precision* for the soil class is 0.98 in calibration, cross-validation, and prediction. Overall model *Accuracy* is 0.98 in calibration and cross-validation and equal to 0.95 in prediction. The obtained results are in line with previous work on MPs.

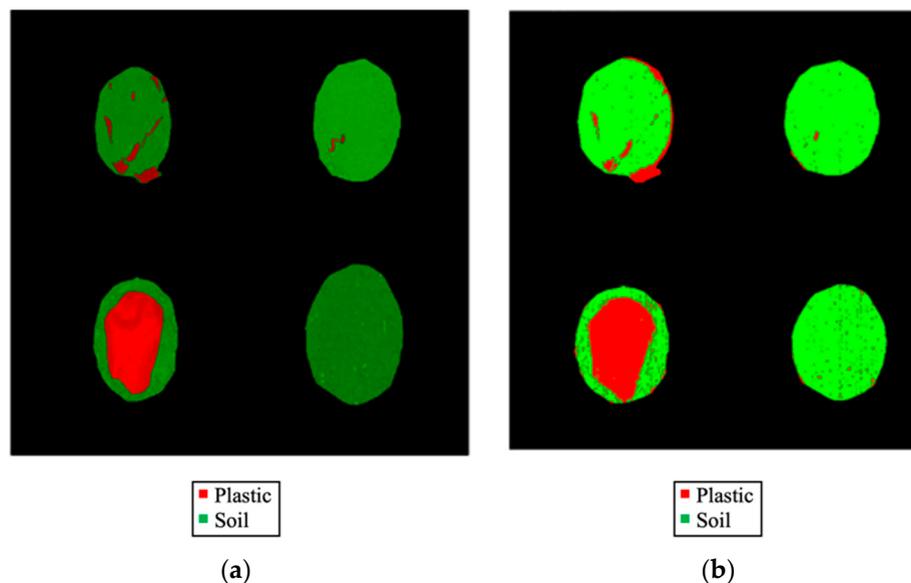


Figure 7. Real classes of the validation set (a) and prediction map obtained from PLS-DA (b).

Table 1. *Sensitivity*, *Specificity*, *Precision*, *Error Rate* and *Accuracy* of the PLS-DA model built for the classification.

Model Phase	Class	<i>Sensitivity</i>	<i>Specificity</i>	<i>Precision</i>	<i>Error Rate</i>	<i>Accuracy</i>
Calibration	Plastic	0.950	0.996	0.988	0.017	0.983
	Soil	0.996	0.950	0.981	0.017	0.983
Cross-validation	Plastic	0.950	0.996	0.988	0.017	0.983
	Soil	0.996	0.950	0.981	0.017	0.983
Validation	Plastic	0.925	0.951	0.786	0.053	0.947
	Soil	0.951	0.925	0.985	0.053	0.947

Ai et al. (2022) proposed a technique based on convolutional neural networks (CNN) and hyperspectral imaging (HSI) technology for recognizing soil microplastic polymers (MPPs) with an *Accuracy* of 0.92 [30].

Chemometrics and FT-NIR spectroscopy were utilized by Paul et al. (2019) to develop a classification model for MPs mixed and non-plastic soil [43]. The SVR and PLS-DA models that were used to identify and classify MP had *Sensitivity* and *Specificity* values of 0.92 and 0.83, and 1.00 and 0.90, respectively.

4. Conclusions and Future Perspectives

This study was carried out to investigate the possibilities of using a hyperspectral imaging system for the on-soil detection of plastic fragments (>5 mm) used for agricultural activities in order to monitor possible MP dispersion. A PLS-DA was set-up to discriminate between plastic and soil. Promising results in classification were achieved. The obtained

Sensitivity and *Specificity* for the different typologies of plastic debris are always greater than 0.92, and the overall model *Accuracy* is 0.95–0.98. The exploratory analysis performed on the spectra of plastic fragments highlighted differences according to their level of aging. Results demonstrated how an NIR-HSI-based approach can be used for the identification of plastic debris in agricultural soils and provide useful information about their level of aging. Such an approach can be regarded as a significant, reliable, fast, and non-invasive procedure for characterizing the end-of-life of plastics used in agricultural activities.

The presented study represents a meaningful starting point for the implementation of a fast, non-invasive, and reliable procedure for the recognition of plastic debris resulting from end-of-life plastics used in agricultural activities. One of the main advantages of this procedure is related to the possibility of being directly applied “in situ” or at laboratory scale. This technique allows rapid data acquisition, enabling efficient and high-throughput analysis of soil samples by dramatically reducing analytical times, which is particularly beneficial for large-scale studies or systematic monitoring applications. Moreover, such a non-destructive technique provides detailed spatial information, enabling the identification and mapping of plastic debris at fine resolution.

On the other side, the limitations of NIR-HSI for plastic detection in soil are mainly connected to the resolution of the instrumentation (e.g., limit of plastic debris size), limitation of depth detection (i.e., plastic detection is difficult for debris that are deep buried since NIR-HSI primarily captures information on or very close to the soil surface), and acquisition conditions in the field (i.e., lighting and sample conditions, as well as environmental variability, can strongly influence NIR-HSI acquisitions). Moreover, changes in soil chemical properties can interfere with the spectral signature of plastic debris, making it difficult to identify plastic signals from background noise or soil-related reflectance spectra. Furthermore, NIR-HSI may not always be suitable for identifying black polymers due to the presence of significant levels of carbon black or soot, which absorb almost all light in the NIR spectral region [44].

Further studies could be addressed to develop classification models able to: (i) detect plastics from different substrates and (ii) strengthen and expand the recognition of the different waste plastics for recycling purposes. Moreover, if fully implemented, the proposed NIR-HSI approach would afford the possibility of developing and implementing it on mobile systems (i.e., Unmanned Ground Vehicles—UGVs or Unmanned Aerial Vehicles—UAVs) capable of performing a full monitoring of plastic waste-related pollution directly at agricultural sites.

Author Contributions: Conceptualization: G.B., S.S., and R.G.; methodology: R.P. and R.G.; software: R.P. and R.G.; validation: G.B., R.P., R.G., E.F., and S.S.; formal analysis: E.F. and R.G.; investigation: G.B., R.P., R.G., E.F., and S.S.; resources: G.B., S.S.; data curation: E.F., R.P., and R.G.; writing—original draft preparation: E.F., R.P., and R.G.; writing—review and editing: G.B., E.F., R.P., and S.S.; visualization: G.B. and S.S.; supervision: G.B. and S.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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